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Published in:
Applied Economics

Publication date:
1987

Applied Economics, 1987, **19**, 1639–1664

Inter-fuel substitution in Dutch manufacturing

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I. INTRODUCTION

In recent years there has been growing interest in the economic consequences of rapidly changing energy prices. Not only has there been interest in the ability of producers to substitute between energy and other inputs such as labour and capital, but also in their ability to substitute one kind of energy for another. The latter question is of importance since, while energy prices have recently been changing relative to the prices of other inputs, the relative prices of the various energy inputs have also been changing. These changes can be expected to result in an alteration in the mix of energy inputs as well as in the share of energy in the total production cost.

This paper is concerned with measuring the substitution and complementarity relationships between four types of energy inputs (coal, oil, gas and electricity) in response to changes in the relative prices of these inputs using annual time-series data for six manufacturing industries in The Netherlands. The paper has two important features that appear to be novel: (i) it makes use of data on six manufacturing industries which enables joint estimatation of the substitution possibilities between fuels at a reasonably disaggregated level, and (ii) the model allows for an error components structure for the vector of disturbances in the factor share equations in which each component is serially correlated.

The only previous attempts to measure the substitution and complementarity relationships between fuels in The Netherlands are by Pindyck (1979) and Griffin (1977). In Pindyck's study aggregate time-series data were used in the estimation, whereas Griffin used aggregate data for twenty countries with four time-series observations for each country. In contrast, the present study uses combined time-series and cross-section data for six separate industries within the Dutch manufacturing sector. It is therefore possible to estimate the effects of changing fuel prices upon the demands for fuel types at a disaggregated industrial level. Specifically, by using disaggregate data it is possible to present matrices of elasticities of substitution and elasticities of demand for each of 6 manufacturing industries. Clearly, such estimates are extremely useful in obtaining a comprehensive understanding of the effects of changes in relative fuel prices upon the industrial structure of the economy.

The studies by Pindyck and Griffin give conflicting evidence on the question of whether gas and coal, and gas and oil are substitutes or complements in The Netherlands. The present results show unambiguously that gas in Dutch manufacturing is a substitute for both coal and oil.

0003–6846/87 $03.00 + .12

The present study assumes that energy inputs are weakly separable from all other inputs and outputs, and focuses upon the estimation of the substitution possibilities between energy types (fuels). It does not deal with the response of total energy demand to changes in input prices. Thus, this study differs from that of Magnus (1979) who measured the substitution and complementarity relationships between energy and non-energy inputs (labour, capital) using aggregate time-series data for The Netherlands.

The second feature of the paper is that the stochastic specification employs a multivariate error components model involving serial correlation. This model specifies that the vector of random disturbances in the system of share equations is composed of a vector which is different for each industry, and a common vector which reflects macro-economic disturbances affecting all industries in the same manner. As a result the disturbances for the different industries are correlated with each other, requiring joint estimation of the share equations for all industries on efficiency grounds. Moreover, both components of the disturbance vectors are assumed to follow first-order autoregressive processes. Thus, the model involves both contemporaneous and inter-temporal correlations between disturbances, and is estimated by the method of maximum likelihood.

The plan of the paper is as follows. In Section II the econometric model of the manufacturing sector is specified and discussed. Section III briefly outlines the nature of the data used in the empirical work. The empirical results are provided in Section IV. The estimates of the parameters of the share equations for the six manufacturing industries are presented and discussed, as are the estimates of the substitution and price elasticities of demands for fuels at the industrial and sectoral levels. Estimates of price indices for energy are also presented for each manufacturing industry. The final section summarizes the results and makes some concluding comments.

II. THE ECONOMETRIC MODEL

The economic model

For the purposes of this study the Dutch manufacturing sector is assumed to consist of q industries each with its own technology. As is well-known (for example, Diewert, 1974; McFadden, 1978), under fairly general conditions the technology may be characterized by the cost function $C^i(\mathbf{p}, \mathbf{y}^i)$, $i = 1, \ldots, q$, which gives the minimum cost of fuel input vectors that are capable of producing net output vector $\mathbf{y}^i$ when $\mathbf{p} = (p_1, \ldots, p_n)'$ is the vector of fuel prices. In this formulation $\mathbf{y}^i$ is a vector of net outputs of non-energy commodities (both inputs and outputs).

To carry out the empirical work, additional structure on the industry cost functions is required. Accordingly, the assumption is made that the industry cost functions take the separable form

$$C^i(\mathbf{p}, \mathbf{y}^i) = c^i(\mathbf{p})h^i(\mathbf{y}^i) \tag{1}$$

for all $\mathbf{p} > 0$ an feasible $\mathbf{y}^i$.

This separability assumption contains structure that is not normally imposed upon a general model of the firm. This structure is exploited in the empirical work. The cost function described by Equation 1 is the product of a function $c^i(\mathbf{p})$ of fuel prices and a function $h^i(\mathbf{y}^i)$ of net outputs of non-energy commodities. This is equivalent to assuming that the vector of fuel inputs $\mathbf{x}^i$ is *homothetically separable* from all other inputs and outputs in the technology.[1] It is well known that the assumption of homothetic separability is necessary and sufficient for a consistent two-stage budgeting or optimization process, whereby the optimal mix of fuel inputs is chosen in the first stage and in the second stage the optimal amount of 'aggregate energy' is chosen along with other variable inputs and outputs.[2] This result is extremely useful since it implies that the substitution possibilities between the various fuel inputs can be investigated without having concern for substitution between fuel inputs and other commodities. Homothetic separability is a standard assumption made in the literature to enable concentration of attention upon a subset of inputs or outputs.

The homothetic separability assumption imposes fairly stringent conditions upon the substitution elasticities, as has been shown by Berndt and Christensen (1973) and Blackorby and Russell (1976). In particular, if the production function is homothetic then the production function is weakly separable in fuels if, and only if, the Allen–Uzawa elasticities of substitution between each fuel and another non-energy input are equal. This does *not* require that the common elasticity of substitution between each fuel and another non-energy input be the same for all other inputs. Accordingly, the assumption of homothetic separability is perfectly consistent with empirical results, such as those of Berndt and Wood (1975) and Magnus (1979), that show energy to be substitutable with labour and complementary with capital.

Under the usual assumptions regarding the cost function, $c^i(\mathbf{p})$ is a positive, continuous, positively linearly homogeneous, concave function of $\mathbf{p} > 0$. In other words, the function $c^i(\mathbf{p})$ satisfies all of the conditions required of a unit cost function. Thus duality theory results may be used to show that it is the unit cost function corresponding to a valid constant returns to scale production function $f^i(\mathbf{x}^i)$. The latter may be interpreted as a quantity index for 'energy' and $c^i(\mathbf{p})$ may be interpreted as a price index for 'energy'.[3]

If the fuel input vector $\mathbf{x}^i$ is chosen to minimize the cost of fuel inputs given the vector of net outputs of other commodities $(\mathbf{y}^i)$ and the price vector for fuel inputs $(\mathbf{p})$, and the function $c^i(\mathbf{p})$ is differentiable, then the cost share of fuel input j in industry i, s^i_j, may be expressed in terms of the unit cost function as

$$s^i_j = \partial \ln c^i(\mathbf{p})/\partial \ln p_j \equiv S^i_j(\mathbf{p}) \tag{2}$$

The importance of this result is that the cost shares are independent of the vector of net outputs of other commodities given by $\mathbf{y}^i$. The cost shares for fuels depend only upon the price vector for fuel inputs.

[1] If $\tilde{F}^i(-\mathbf{x}^i, \mathbf{y}^i) = 0$ is the transformation frontier denoting the boundary of the production set T^i then it is assumed that $\tilde{F}^i(-\mathbf{x}^i, \mathbf{y}^i) = F^i(-f^i(\mathbf{x}^i), \mathbf{y}^i)$ where $f^i(\mathbf{x}^i)$ is a homothetic function which aggregates fuel inputs. The aggregator function $f^i(x^i)$ may be interpreted as a quantity index for the fuel inputs and hence be called 'energy'.

[2] The sufficiency of this condition was established by Shephard (1970, pp. 143–6). That the condition is also necessary follows from the duality between production and cost functions.

[3] See Diewert (1974) for details on the duality between production and cost functions under constant returns to scale.

Given a functional form for the unit cost function, the share equations can therefore be obtained by logarithmic differentiation as in Equation 2. The present empirical model uses the translog function due to Christensen *et al.* (1973):

$$\ln c^i(\mathbf{p}) = b^i_{..} + \sum_{j=1}^{n} b^i_{.j} \ln p_j + \frac{1}{2} \sum_{j=1}^{n} \sum_{k=1}^{n} b^i_{kj} \ln p_k \ln p_j \tag{3}$$

where the following parametric restrictions are imposed:

$$b^i_{kj} = b^i_{jk} \qquad k, j = 1, \ldots, n$$

$$\sum_{j=1}^{n} b^i_{.j} = 1$$

$$\sum_{j=1}^{n} b^i_{kj} = 0 \qquad k = 1, \ldots, n. \tag{4}$$

The corresponding share equations have the convenient linear form

$$s^i_j(\mathbf{p}) = b^i_{.j} + \sum_{k=1}^{n} b^i_{kj} \ln \mathbf{p}_k \qquad j = 1, \ldots, n;\ i = 1, \ldots, q \tag{5}$$

Data on prices and costs shares enable estimation of all of the parameters of the share equations which involve all of the parameters of the unit cost function with the exception of $b^i_{..}$. That is, the cost function is only identified up to a factor of proportionality by the share equations.

The preceding formulation of the model assumes that the industry production sets and hence the cost functions are given and invariant over time. In general if technical change takes place over time the share equations will depend upon time. However, assume that technical change is Hicks-neutral which, under the homotheticity assumption, implies that the technical change simply transforms the $f^i(\mathbf{x}^i)$ functions and their corresponding unit cost functions $c^i(\mathbf{p})$ linearly. Accordingly, the share equations are unaffected by technical change which can therefore be ignored.

Elasticities

The substitution possibilities may be described by various elasticities. Below estimates of the Allen–Uzawa substitution elasticities are reported which, in the case of the translog function, are

$$\sigma^i_{kj} = c^i(\mathbf{p})c^i_{kj}(\mathbf{p})/c^i_k(\mathbf{p})c^i_j(\mathbf{p}) = 1 + (b^i_{kj} - \delta_{kj}S^i_j)/S^i_k S^i_j \tag{6}$$

where $\delta_{kj} = 0$ if $k \neq j$ and $\delta_{kk} = 1$; $c^i_j(\mathbf{p}) \equiv \partial c^i(\mathbf{p})/\partial p_j$; and $c^i_{kj}(\mathbf{p}) \equiv \partial^2 c^i(\mathbf{p})/\partial p_k \partial p_j$. The price elasticities are also reported

$$\eta^i_{kj} \equiv \partial \ln x^i_k / \partial \ln p_j = \sigma^i_{kj} S^i_j \tag{7}$$

which indicate the percentage change in the demand for fuel k due to a 1% change in the price of fuel j when all other prices and the index of total energy use, $f^i(\mathbf{x}^i)$, are held constant. These elasticities are allowed to be different over the industries. To obtain a measure of the overall (sector) substitution effects the corresponding 'market' or aggregate sector elasticities are also calculated. These are obtained by defining $x_k = \sum_{i=1}^{q} x_k^i$ as the quantity of fuel k used in all industries and performing the required differentiation to get

$$\sigma_{kj} = \sum_{i=1}^{q} \sigma_{kj}^i w_k^i w_j^i / \theta^i \tag{8}$$

and

$$\eta_{kj} \equiv \partial \ln x_k / \partial \ln p_j = \sum_{i=1}^{q} \eta_{kj}^i w_k^i \tag{9}$$

where $w_k^i \equiv \mathrm{x}_k^i / \mathrm{x}_k$ is the share of industry i in the use of fuel k and

$$\theta^i \equiv \sum_{j=1}^{n} p_j x_j^i \Big/ \sum_{l=1}^{q} \sum_{j=1}^{n} p_j x_j^l \tag{10}$$

is the share of industry i in the energy cost of production for the whole sector. These 'market' elasticities represent the response of the total demand for fuel k to a change in the price of fuel j when all other prices and the total energy use index in each industry remains constant. Note that the market price elastiticities Equation 9 are weighted averages of the corresponding industry price elasticities, while the market Allen elasticities σ_{kj} given by Equation 8 are not weighted averages of the σ_{kj}^i.

Stochastic specification

The econometric model is obtained by adding a time subscript t to the cost share Equation 5 and embedding the model in a stochastic framework, as follows

$$\mathrm{s}_{jt}^i = \mathrm{b}_{.j}^i + \sum_{k=1}^{n} \mathrm{b}_{kj}^i \ln p_{kt} + u_{jt}^i \qquad j = 1, \ldots, n \equiv 4;\ i = 1, \ldots, q \equiv 6;$$
$$t = 1, \ldots, T \equiv 19. \tag{11}$$

Since we are dealing with shares, the disturbances are constrained by $\sum_{j=1}^{n} u_{jt}^i = 0$. This implies that it is possible arbitrarily to drop one of the n equations, say the last, in each year and for each industry (see e.g. Barten, 1969). Incorporating the parameter restrictions (Equation 4) and dropping one full share equation, Equation 11 can be written as:

$$\mathrm{s}_t^i = \mathrm{X}_t \beta^i + \mathbf{u}_t^i \qquad i = 1, \ldots, q;\ t = 1, \ldots, T \tag{12}$$

where s_t^i and $\mathbf{u}_t^i$ are 3-dimensional vectors, β^i is a 9-dimensional vector consisting of the independent parameters of the share equations, and X_t is a 3×9 matrix of regressors (functions of input prices).

The parameters of Equation 12 shall be estimated by the method of maximum likelihood (ML), assuming that the disturbances u_{jt}^i follow a multivariate normal distribution with mean 0 and some covariance matrix. Let us now briefly discuss the specification of the covariance structure of the random disturbances.

As a starting point, assume that the $(n-1)$ dimensional disturbance vectors $\mathbf{u}_t^i$ are independently distributed as

$$\mathbf{u}_t^i \simeq \mathrm{NI}(0, \Delta_i)$$

where $\Delta_1, \ldots, \Delta_q$ are unknown positive definite $(n-1) \times (n-1)$ matrices.[4] This implies that the q industries can be analysed completely independently of each other. Maximum likelihood estimation of the β^i and Δ_i parameters leads to ML estimates $\tilde{\beta}_i$ and $\tilde{\Delta}_i$. From these estimates three conclusions emerge. First, the six (q) $\tilde{\Delta}_i$ matrices appear to have the same pattern; in fact they are close to being equal to each other apart from a factor of proportionality.[5] Secondly, from the residuals $\tilde{\mathbf{u}}_t^i = \mathrm{y}_t - \mathrm{X}_t\tilde{\beta}^i$ we can compute the cross-correlation matrices $\tilde{\Delta}_{ij} = (1/T)\sum_{t=1}^{T} \tilde{\mathbf{u}}_t^i(\tilde{\mathbf{u}}_t^j)'$, $(i \neq j)$. These appear to be significantly different from zero.[6] Both conclusions suggest that significant contemporaneous inter-industry correlations are present. Thirdly, and not surprisingly, the residuals show a high degree of autocorrelation.[7]

In principle it is possible to estimate an *unrestricted* $q(n-1) \times q(n-1) = 18 \times 18$ contemporaneous covariance matrix (171 parameters) with autocorrelation (6 parameters). Together with the $6 \times 9 = 54$ parameters in the β^i's, this would bring the total number of parameters to 231. Since there are only 342 observations $(6 \times 19 \times 3)$, this leaves few degrees of freedom.[8] Hence a more attractive solution needs to be found.

Thus it is sought to combine cross-correlation (between industries) and autocorrelation (over time) in such a way that ML estimation of the full model (Equation 12) is feasible. This, it is held, is achieved by employing the assumption that the disturbance vector, $\mathbf{u}_t^i$, has a multivariate two error components structure in which each component is serially correlated. More specifically, it is assumed that the disturbance vectors $\mathbf{u}_t^i$ decompose as

$$\mathbf{u}_t^i = \mathbf{e}_t + \varepsilon_t^i,$$

[4]Strictly speaking one should assume a distribution for the shares which contrains them to be between zero and one. While the normal distribution does not impose this restriction *a priori*, there is some evidence that it is still appropriate as an approximation. See Woodland (1979).

[5]The range of the factor of proportionality is 0.57 to 5.00.

[6]The average cross-correlation matrix is

$$\frac{1}{q(q-1)}\sum_{i \neq j} \tilde{\Delta}_{ij} = 0.0158 \begin{bmatrix} 0.05 & -0.08 & 0.04 \\ -0.08 & 0.61 & -0.45 \\ 0.04 & -0.45 & 0.34 \end{bmatrix}$$

and the average own correlation matrix is

$$\frac{1}{q}\sum_{i} \tilde{\Delta}_{ii} = 0.0202 \begin{bmatrix} 0.07 & -0.10 & 0.03 \\ -0.10 & 0.60 & 0.42 \\ 0.03 & 0.42 & 0.32 \end{bmatrix}$$

[7]Re-estimating the q models with first-order autocorrelation yields the following ML estimates for the autocorrelation parameters: 0.93(FOOD), 0.93(TEXT), 0.92(PAPR), 0.68(CHEM), 0.88(BLDG), 0.89(METL).

[8]See also Deaton (1975, pp. 50–53).

where

$$\mathbf{e}_t = \rho \mathbf{e}_{t-1} + \mathbf{v}_t \qquad |\rho| < 1$$

and

$$\varepsilon_t^i = \alpha \varepsilon_{t-1}^i + \lambda_i^{1/2} \eta_t^i \qquad |\alpha| < 1, \lambda_i > 0 \; (i = 1, \ldots, q).$$

The vectors $\mathbf{v}_t$ are i.i.d. N(0, Γ), Γ positive semidefinite; the vectors η_t are i.i.d. N(0, Δ), Δ positive definite; and $\mathbf{v}_t$ and η_t^i are independent.

The disturbance vectors $\mathbf{u}_t^i$ are thus composed of a vector which is different for each industry and time period, and a common vector (varying only over time), which reflects macro-economic disturbances affecting all industries in the same manner. The error component ε_t^i varies over time and industry and represents the usual vector of disturbances arising from optimization errors on the part of firms. If $\alpha = 0$ for simplicity, the covariance matrix for ε_t^i is $\lambda_i \Delta$, which varies over industries according to the proportionality parameter λ_i. Thus, the stochastic specification is between the extreme cases of completely free covariance matrices and a common covariance matrix for each industry, and is consistent with preliminary empirical results reported above. The time specific component $\mathbf{e}_t$ represents shocks to the fuel shares that are of an economy-wide nature, and is assumed to be identical for each industry. Both error component vectors can be subject to autocorrelation. While it would be desirable to allow the autocorrelation parameter α to vary by industry, the special structure of the full covariance matrix for the disturbances that allows simplification of the calculation of its inverse and determinant, so making ML estimation of the model feasible, would then be lost. Accordingly, the assumption is maintained that α is the same for every industry. Further details of this stochastic specification, together with a derivation of the maximum likelihood estimator, are available in Magnus and Woodland (1987a).

III. CHARACTERISTICS OF THE DATA

Let us now look at the data. The time period for this study is from 1958 to 1976, for this is the period during which the quantity data collected by the Netherlands Central Bureau of Statistics were available. Four types of energy are distinguished: (i) solid fuels (COAL); (ii) liquid fuels (OIL); (iii) natural and manufactured gas (GAS); and (iv) electricity (ELEC). Figure 1 shows the variation of these four energy types in Dutch manufacturing over the observed period. The price of oil relative to the price of gas ranged from a minimum of 0.26 (in 1960) to a maximum of 2.13 (in 1974), an increase by a factor of eight. The price of oil relative to electricity ranged from 0.11 to 0.41, while the price of oil relative to coal ranged from 0.43 to 0.90. These changes can be expected to result in an alteration in the mix of energy inputs as well as in the share of energy in the total production cost.

Six industries of the Dutch manufacturing sector are also distinguished: (i) food, beverages and tobacco products (FOOD); (ii) textiles (TEXT); (iii) paper and paper products (PAPR); (iv) chemical industry (CHEM); (v) building materials, earthenware, glass and glass products (BLDG); and (vi) fabricated metal products, transport equipment, and mechanical and

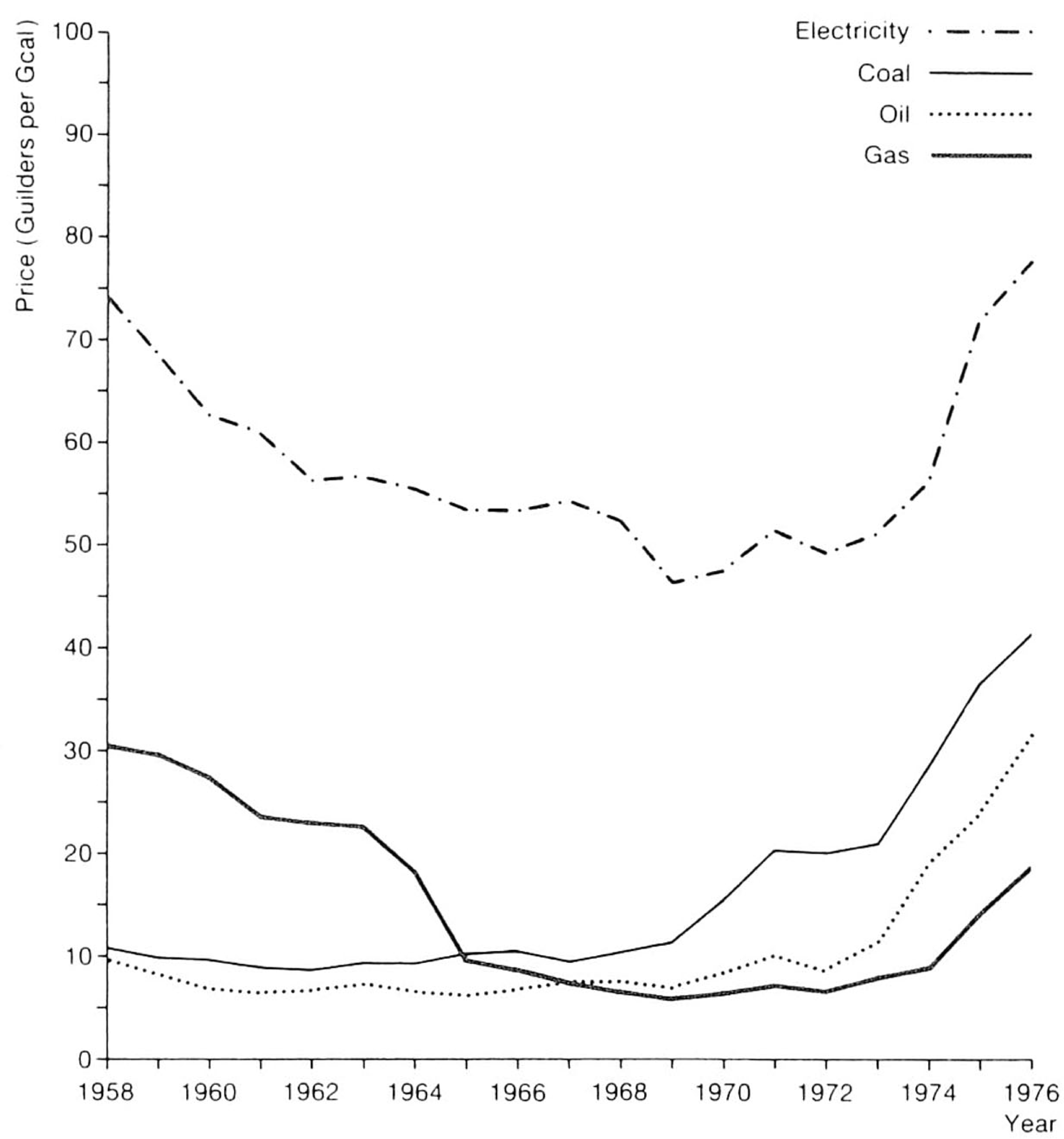

Fig. 1. Prices of coal, oil, gas and electricity in the Netherlands, 1958–76 (guilders per Gcal).

electrical engineering (METL). The six industries combined account for roughtly 75 % of Dutch manufacturing output.[9] Data requirements prohibit further disaggregation.

Under the assumption that each industry faces the same energy prices, the estimation requires data for price indices of COAL, OIL, GAS, and ELEC, and input costs for each of the four energy types in each industry. Data were drawn from publications by the Netherlands Central Bureau of Statistics.[10] The data used in the present study are presented in the Appendix. Prices and quantities are measured in Gcal (1 gigacalorie = 10^9 calories). The major difficulty was to ensure that energy inputs are only labelled as such when they are used as energy, and *not* as raw materials. This problem arose in the chemical industry with the production of naphtha – where only 5 % of the oil input is used as energy – and synthetic fertilizers.

[9]The main industry left out is the basic metal industry. From 1958–68 this industry was a net producer of gas. Since the aim was to concentrate upon the demand for the inputs of energy, rather than on their supplies, the basic metal industry did not fit into the framework.
[10]A full documentation and discussion of the data (in Dutch) is provided in Magnus and Vastenou (1978).

Energy consumption in Dutch manufacturing has increased considerably during the observed period: in 1976 the demand for energy was more than three times as large as in 1958. Also, the distribution over the various energy types has changed drastically. Before 1958, coal was the cheapest per Gcal of the three primary energy inputs, coal, oil and gas. During the period 1958–66, oil was cheaper than coal and gas. After 1966, the discovery and exploitation of the natural gas field in Slochteren made gas the cheapest input. Table 1 summarizes how the demand has reacted to these relative price changes. The substitution away from coal, in favour of gas is remarkable.

Finally, let us consider the development of each of the six industries over time. Table 2 shows that the relative importance of the chemical industry (measured by its energy expenditures) rose substantially, while the energy share of the textile industry fell due to the dramatic decline of that industry's output.

Table 1. *Quantity and cost shares of energy in Dutch manufacturing, 1958–76*[a]

	Quantity shares				Cost shares			
	COAL	OIL	GAS	ELEC	COAL	OIL	GAS	ELEC
1958	0.40	0.47	0.05	0.08	0.26	0.27	0.09	0.38
1967	0.08	0.60	0.21	0.11	0.06	0.35	0.12	0.47
1976	0.02	0.26	0.64	0.08	0.03	0.30	0.44	0.23

[a]'Dutch manufacturing' denotes the aggregate of FOOD, TEXT, PAPR, CHEM, BLDG and METL.

Table 2. *Exenditures on energy for six manufacturing industries (percentages of total)*

	FOOD	TEXT	PAPR	CHEM	BLDG	METL
1958	0.21	0.10	0.09	0.32	0.13	0.15
1967	0.18	0.06	0.09	0.40	0.13	0.14
1976	0.13	0.02	0.05	0.65	0.08	0.07

IV. EMPIRICAL RESULTS

Parameter estimates

The full model was estimated by the method of maximum likelihood.[11] The β^i estimates are presented together with the estimates of their asymptotic standard errors in Table 3.

One half of the estimated coefficients appear to be statistically 'significant' (although only 40% of the sixty b^i_{kj} coefficients is significant), which is of importance not only for the significance of the implied elasticities (to be discussed in the next section), but also because b^i_{kj}

[11]The ML estimates were obtained using the quasi-Newton algorithm by Fletcher (1972).

Table 3. *Parameter estimates for translog cost functions*[a]

	FOOD	TEXT	PAPR	CHEM	BLDG	METL
b_C	0.1030	0.0927	0.1468	0.0578	0.2076	0.0671
	(0.0424)	(0.0417)	(0.0469)	(0.0490)	(0.0420)	(0.0430)
b_O	0.3088	0.2376	0.2216	0.1643	0.1914	0.1339
	(0.0862)	(0.0857)	(0.0896)	(0.0912)	(0.0859)	(0.0866)
b_G	0.2071	0.1523	0.2533	0.2742	0.2910	0.1498
	(0.0856)	(0.0853)	(0.0875)	(0.0885)	(0.0855)	(0.0859)
b_E	0.3811	0.5174	0.3784	0.5037	0.3100	0.6492
	(0.0278)	(0.0270)	(0.0330)	(0.0354)	(0.0274)	(0.0286)
b_{CC}	−0.0157	−0.0242	−0.0819	0.0603	−0.0822	0.0162
	(0.0430)	(0.0406)	(0.0574)	(0.0634)	(0.0417)	(0.0452)
b_{CO}	−0.0683	−0.0605	−0.0510	−0.0519	−0.0453	−0.0205
	(0.0407)	(0.0384)	(0.0547)	(0.0605)	(0.0395)	(0.0429)
b_{CG}	0.0832	0.0597	0.1398	0.0519	0.0893	0.0009
	(0.0237)	(0.0227)	(0.0299)	(0.0325)	(0.0232)	(0.0246)
b_{CE}	0.0007	0.0250	−0.0069	−0.0603	0.0382	0.0034
	(0.0271)	(0.0254)	(0.0369)	(0.0410)	(0.0262)	(0.0286)
b_{OO}	0.0604	0.1320	0.0695	0.2489	0.1049	0.1142
	(0.0614)	(0.0589)	(0.0771)	(0.0839)	(0.0600)	(0.0637)
b_{OG}	0.0470	0.0291	0.0253	−0.0165	0.0063	0.0044
	(0.0428)	(0.0421)	(0.0480)	(0.0504)	(0.0424)	(0.0436)
b_{OE}	−0.0391	−0.1006	−0.0438	−0.1805	−0.0660	−0.0982
	(0.0259)	(0.0241)	(0.0362)	(0.0404)	(0.0249)	(0.0275)
b_{GG}	−0.0386	−0.0109	−0.0944	0.0200	−0.0263	0.0830
	(0.0424)	(0.0419)	(0.0459)	(0.0475)	(0.0421)	(0.0429)
b_{GE}	−0.0915	−0.0779	−0.0707	−0.0555	−0.0693	−0.0883
	(0.0185)	(0.0175)	(0.0252)	(0.0279)	(0.0180)	(0.0196)
b_{EE}	0.1300	0.1535	0.1214	0.2963	0.0971	0.1831
	(0.0303)	(0.0285)	(0.0415)	(0.0462)	(0.0293)	(0.0321)

[a]Asymptotic standard errors are in parentheses. Fuels are indicated C = coal, O = oil, G = gas, E = electricity.

has an economic interpretation for its own sake: it indicates the change in the kth cost share resulting from a 1% change in the jth energy price.[12] Thus, from Table 3, the parameter estimates imply that higher coal prices will lead to a higher cost share for gas; higher prices of oil will reduce the cost share for electricity; higher gas prices will lead to a higher cost share for coal, but to a lower cost share for electricity; higher electricity prices result in lower cost shares for oil and gas, and in a higher cost share for electricity. On the other hand, an increase in the price of oil will have no significant effect on the cost share of gas (and vice versa, since $b_{OG} = b_{GO}$) in any of the six industries.

[12]Here, and in what follows, statistically 'significant' means that the absolute value of the parameter estimate divided by the estimate of its asymptotic standard error exceeds 1.96. Since there are only 19 years of observations, it is doubtful if the asymptotic theory would hold. Thus the word 'significant' must be used with caution.

For the empirical cost function and the resulting cost share equations to be consistent with cost minimization, the estimated cost shares must be positive (for all years, industries and energy types), and the estimated cost function must be concave (for all years and industries). All estimated cost shares for coal, oil, gas and electricity were positive over the whole sample period and in every industry, even though the use of gas before 1963 and the use of coal after 1971 was very small, so that the observed cost shares for gas and coal in the relevant years were also very small (0.01 or even smaller). Concavity of the cost function was checked at the observed prices for each of the nineteen years and six industries by checking for a negative semidefinite Hessian matrix. Of the 114 (namely 6×19) calculated Hessians, 80 are negative semidefinite.[13] A necessary, but not sufficient, condition for the Hessian to be negative semidefinite is that its diagonal elements, indicating the response of an input to a change in its own price, are non-positive. Closer inspection of the Hessian matrices revealed that 89 % of the diagonal elements are negative.[14] The violations appear, therefore, not too severe.

The conventional goodness of fit statistic, R^2, was calculated for each fuel in each industry, and the results are reported in Table 4.[15] Since the conventional R^2 values are based upon residuals $\tilde{\mathbf{u}}_t^i = \mathbf{s}_t^i - X_t\beta^i$, they do not take account of the 'explanation' provided by the autoregression process. They therefore represent the explanation of shares provided by variations in relative fuel prices. The fit seems reasonably good for coal, gas and electricity (with the exception of the PAPR industry), but not for oil. For oil the goodness of fit as measured by R^2 is uniformly low in all industries.

Because of the existence of serial correlation in the components of the disturbances, the best linear unbiased predictor of $\mathbf{s}_t^i$ is not $X_t\tilde{\beta}^i$ but $X_t\tilde{\beta}^i + \mathbf{a}_t^i$, where $\mathbf{a}_t^i$ depends upon the covariance matrix for the disturbances and all disturbances prior to t.[16] Using this predictor for $\mathbf{s}_t^i$ 'adjusted' R^2 values were calculated, reflecting the explanatory power of the autoregression processes as well as the fuel prices, and these are presented in the second row of each cell in Table 4. The adjusted R^2 values are all higher than the corresponding unadjusted R^2 values. In particular, the adjusted R^2 values for oil, with the exception of the CHEM industry, are now fairly high. Clearly, the autoregression processes are contributing significantly to the explanation of fuel shares, particularly oil.[17]

[13]In the FOOD, PAPR, and BLDG industries the Hessians are negative semidefinite in every year, in the TEXT industry in every year but one (1972), in the METL industry only in 1971 and 1973–76, while the Hessian matrix in the CHEM industry fails to be negative semidefinite in any year of the sample period.

[14]It was found that the response of coal to a change in its own price has the wrong sign (positive) in 2 cases (out of a possible 114), oil in 27 cases, and electricity in 19 cases, while an increase in the gas price always reduced the demand for gas. Most violations occur in the CHEM industry; the remainder in the METL industry.

[15]R^2 is defined here as unity minus the ratio of the sample variance of the residuals ($\hat{u}_{jt}^i$) to the sample variance of the shares (s_{jt}^i). As is well known, the range of R^2 is the interval $(-\infty, 1]$ since the residuals in a particular equation do not necessarily sum to zero over t.

[16]The formula for the best linear unbiased predictor in a linear model with known variance matrix is given in Johnston (1972, p. 213), for example. In the present context, the adjustment term $\mathbf{a}_t^i$ depends in a complex manner, on all covariance matrix parameters.

[17]The estimates of the two autocorrelation parameters $\tilde{\alpha} = 0.74$ and $\tilde{\rho} = 0.94$ are both highly significant, thus firmly rejecting the hypothesis of time independence.

Table 4. R^2 *values*[a]

	FOOD	TEXT	PAPR	CHEM	BLDG	METL
COAL	0.73	0.70	0.83	0.41	0.85	−0.05
	0.85	0.90	0.93	0.77	0.95	0.83
OIL	0.15	−0.37	−0.05	−1.05	−0.38	−1.30
	0.89	0.82	0.86	0.34	0.82	0.69
GAS	0.57	0.46	0.59	0.18	0.46	−0.18
	0.93	0.91	0.94	0.81	0.92	0.83
ELEC	0.73	0.83	−0.79	0.94	0.84	0.86
	0.83	0.85	0.39	0.95	0.89	0.86

[a]The first figure in each cell is the R^2 based upon residuals $\hat{\mathbf{u}}_t^i$. The second is the 'adjusted R^2', which takes account of serial correlation.

The importance of the autoregression processes and the literature on dynamic factor demand functions suggest the possibility that the autoregression processes constitute a proxy for a lagged adjustment process. However, the formulation of dynamic demand functions for fuels consistent with economic theory, along the lines set out by Epstein (1981), and their estimation in the context of an error components structure for disturbances is extremely complex and is beyond the scope of this paper.

Allen–Uzawa substitution and price elasticities

From the parameter estimates in Table 3 together with the estimated cost shares, it is possible to calculate Allen–Uzawa substitution and price elasticities by Equations 6 and 7. Since prices change from year to year, so do the estimated elasticities. Space limitations, however, force presentation of these elasticities for one year only. Thus, in Tables 5 and 6, price and Allen–Uzawa substitution elasticities are presented for the final sample year, 1976. The first six columns in Tables 5 and 6 give the estimated elasticities for each industry separately. Two aggregates have been estimated: MARKET and TOTAL. The MARKET elasticities are computed from Equations 8 and 9, while the TOTAL elasticities are obtained by estimating a single translog cost function for the manufacturing sector as a whole, assuming a separable structure for the sectoral cost function.[18, 19] These are the estimates that would be obtained if only aggregate data for the manufacturing sector were available and the homothetic separability assumption were invoked at the sectoral level of aggregation.[20]

[18]The weights w_k^i and θ^i in Equations 8 and 9 cannot be estimated from the present cost share model. Therefore their observed values were used in calculating MARKET elasticities.
[19]The method of estimation was again maximum likelihood, and the covariance specification was seemingly unrelated regressions with autocorrelation.
[20]These estimates are therefore different from those that would be obtained from the error components model under the assumption that the parameter vectors β^i are the same in each industry, since in the latter case information on industry shares is used.

Table 5. *Estimated price elasticities*[a]

	Own-price elasticities				Effects of a 1% change in the price of coal			Effects of a 1% change in the price of oil			Effects of a 1% change in the price of gas			Effects of a 1% change in the price of electricity		
	η_{CC}	η_{OO}	η_{GG}	η_{EE}	η_{OC}	η_{GC}	η_{EC}	η_{CO}	η_{GO}	η_{EO}	η_{CG}	η_{OG}	η_{EG}	η_{CE}	η_{OE}	η_{GE}
FOOD	−1.20	−0.49	−0.79	−0.26	−0.15	0.31	0.06	−0.82	0.47	0.19	1.73	0.47	0.01	0.30	0.17	0.01
	(0.80)	(0.21)	(0.14)	(0.11)	(0.15)	(0.11)	(0.09)	(1.20)	(0.15)	(0.12)	(1.27)	(0.22)	(0.12)	(0.47)	(0.09)	(0.10)
TEXT	−1.66	−0.27	−0.80	−0.22	−0.15	0.28	0.10	−1.41	0.45	0.07	1.96	0.33	0.05	1.11	0.09	0.07
	(1.60)	(0.17)	(0.17)	(0.07)	(0.14)	(0.13)	(0.07)	(2.63)	(0.17)	(0.10)	(2.48)	(0.20)	(0.10)	(1.32)	(0.10)	(0.14)
PAPR	−1.94	−0.47	−0.87	−0.29	−0.12	0.45	0.06	−0.38	0.32	0.10	2.12	0.48	0.13	0.20	0.11	0.10
	(1.07)	(0.30)	(0.16)	(0.16)	(0.24)	(0.13)	(0.12)	(0.86)	(0.13)	(0.14)	(1.28)	(0.27)	(0.13)	(0.45)	(0.15)	(0.09)
CHEM	−0.29	0.05	−0.61	0.61	−0.04	0.26	−0.19	−0.17	0.31	−0.48	0.85	0.28	0.06	−0.40	−0.28	0.04
	(0.67)	(0.21)	(0.14)	(0.38)	(0.19)	(0.11)	(0.20)	(0.74)	(0.15)	(0.26)	(0.52)	(0.19)	(0.16)	(0.43)	(0.15)	(0.10)
BLDG	−1.58	−0.33	−0.69	−0.36	−0.06	0.35	0.28	−0.12	0.27	−0.01	1.14	0.41	0.10	0.56	−0.01	0.06
	(0.50)	(0.22)	(0.12)	(0.13)	(0.18)	(0.09)	(0.11)	(0.40)	(0.12)	(0.13)	(0.43)	(0.22)	(0.12)	(0.29)	(0.12)	(0.07)
METL	−0.68	−0.28	−0.39	−0.13	−0.02	0.07	0.07	−0.09	0.26	0.04	0.22	0.22	0.02	0.55	0.08	0.06
	(0.70)	(0.25)	(0.26)	(0.06)	(0.20)	(0.12)	(0.06)	(0.76)	(0.20)	(0.10)	(0.41)	(0.24)	(0.10)	(0.47)	(0.18)	(0.22)
TOTAL	−1.84	−0.33	−0.92	−0.24	−0.09	0.35	0.08	−0.78	0.48	0.09	1.99	0.33	0.07	0.63	0.09	0.09
	(1.06)	(0.17)	(0.29)	(0.09)	(0.11)	(0.13)	(0.07)	(1.08)	(0.22)	(0.13)	(1.01)	(0.26)	(0.13)	(0.72)	(0.12)	(0.15)
MARKET	−0.55	−0.02	−0.66	0.16	−0.05	0.28	−0.04	−0.20	0.33	−0.18	0.89	0.30	0.05	−0.14	−0.22	0.04
Griffin	−0.48	−2.37	−1.65	—	1.69[b]	−0.26[b]	—	0.51	1.91	—	−0.03	0.68[b]	—	—	—	—
	(0.18)	(1.04)	(0.33)					(0.27)	(0.87)		(0.02)					
Pindyck	−1.67	−0.11	−1.42	−0.07	0.20	1.84	0.09	0.21	−0.21	0.00	0.98	−0.10	−0.02	0.48	0.01	−0.22
	(0.22)	(0.15)	(0.13)	(0.02)	(0.15)	(0.16)	(0.02)	(0.16)	(0.15)	(0.02)	(0.09)	(0.07)	(0.01)	(0.11)	(0.08)	(0.09)

[a]All elasticities from the present study are calculated in the last year of the sample, 1976. Asymptotic standard errors are in parentheses.
[b]These estimates were not presented by Griffin and have been calculated indirectly.

Table 6. *Estimates of Allen–Uzawa substitution elasticities*[a]

	Own-Allen elasticities				Cross-Allen elasticities					
	σ_{CC}	σ_{OO}	σ_{GG}	σ_{EE}	σ_{OC}	σ_{GC}	σ_{EC}	σ_{GO}	σ_{EO}	σ_{EG}
FOOD	−20.24	−1.51	−2.41	−0.90	−2.54	5.27	1.04	1.44	0.58	0.03
	(24.59)	(0.93)	(0.98)	(0.35)	(3.84)	(3.51)	(1.58)	(0.41)	(0.29)	(0.34)
TEXT	−47.55	−0.82	−3.29	−0.55	−4.28	8.03	2.82	1.36	0.22	0.19
	(98.43)	(0.62)	(1.57)	(0.17)	(8.18)	(9.39)	(3.28)	(0.52)	(0.26)	(0.35)
PAPR	−24.13	−1.86	−2.27	−1.02	−1.50	5.56	0.70	1.26	0.39	0.35
	(26.75)	(1.59)	(0.90)	(0.48)	(3.49)	(3.06)	(1.57)	(0.51)	(0.52)	(0.28)
CHEM	−2.93	0.13	−1.89	2.85	−0.45	2.63	−1.89	0.86	−1.33	0.20
	(6.52)	(0.59)	(0.75)	(2.26)	(2.04)	(1.43)	(2.08)	(0.43)	(0.80)	(0.47)
BLDG	−13.28	−1.30	−1.80	−1.47	−0.48	2.97	2.33	1.06	−0.06	0.25
	(8.61)	(1.02)	(0.67)	(0.46)	(1.60)	(0.96)	(1.10)	(0.44)	(0.50)	(0.27)
METL	−10.72	−1.19	−1.92	−0.27	−0.36	1.07	1.11	1.09	0.16	0.12
	(13.24)	(1.16)	(0.97)	(0.12)	(3.24)	(1.92)	(0.93)	(0.91)	(0.36)	(0.43)
TOTAL	−42.16	−0.90	−3.66	−0.71	−2.16	7.92	1.84	1.32	0.26	0.28
	(39.04)	(0.59)	(1.59)	(0.26)	(3.00)	(4.38)	(2.05)	(0.69)	(0.33)	(0.46)
MARKET	−6.93	0.05	−2.10	0.44	−0.56	2.71	−0.35	0.89	−0.76	0.18
Griffin	−0.67	−11.05	−21.42	—	2.38	−0.38	—	8.87	—	—
Pindyck	−12.86	−0.77	−20.44	−0.11	1.51	14.14	0.71	−1.46	0.01	−0.31

[a] All elasticities from the present study are calculated in the last year of the sample, 1976. Asymptotic standard errors are in parentheses. The estimates from Griffin's and Pindyck's studies were not presented by them, and have been calculated indirectly from the estimated price elasticities.

It is clear from Tables 5 and 6 that the TOTAL elasticities (obtained by assuming separability at the sectoral level) and the MARKET elasticities (which arise from the disaggregated model) are quite far apart. Hence, even if one is interested only in elasticities for the manufacturing sector as a whole, it is important, at least for this body of data, to estimate a disaggregated model.[21]

Concentrating first on the MARKET elasticities, presented in Table 7 are price elasticities for three selected years. In The Netherlands, as natural gas prices fell, there was a large increase in the share of natural gas (from almost zero) as supplies became available for the first time (around 1966). Also, as coal prices increased, there was a decrease in the share of coal (to almost zero) after the shutdown of Dutch coal mines. This might tend to bias the natural gas and coal elasticities upwards. It is found, indeed, that the own-price elasticities for coal and gas are particularly high. Oil seems less sensitive to a change in its own price. Not surprisingly, the own-price elasticity for electricity is also quite small: electricity is much more expensive on a thermal basis than the other three fuels, and should therefore only be used when there is little possibility of using an alternative fuel.

Looking now at the cross-price elasticities of the MARKET aggregate, it can be seen that gas and coal are unambiguous substitutes. Indeed, coal has suffered more than other fuels from the low gas prices. On the other hand, increasing gas prices may lead to a profitable re-opening of the Dutch coal mines. Oil and gas are also substitutes though less significantly. In 1967, for example, a 1 % increase in the price of gas relative to the prices of other fuels would imply a 0.28 % higher demand for oil. While gas appears to be a substitute for both coal and oil, Table 7 shows that coal and oil are complements, if only moderately so. There is some evidence that the demand for electricity in Dutch manufacturing reacts differently to price changes in coal, oil, and gas. Gas and electricity are substitutes, but the impact of price changes in coal and oil on electricity demand is not clear.

Let us now briefly compare the aggregate results with two other studies on inter-fuel substitution possibilities in The Netherlands. Griffin (1977) estimated a translog model using a pooled international sample, consisting of observations for twenty OECD countries for five year intervals (1955, 1960, 1965, 1969), while Pindyck (1979) estimated a translog model using pooled time-series data (1959–73) for a cross-section of ten countries. Both studies include The Netherlands in their sample. Tables 5 and 6 show that the estimated elasticities of the three studies are quite far apart, both in magnitude and in sign. For example, Griffin finds gas and coal to be complements in The Netherlands, while Pindyck finds them to be substitutes. On the other hand, Pindyck's estimates indicate that gas and oil are complements, while Griffin's indicate that they are substitutes. The present study shows significant substitution possibilities between gas and coal, as well as between gas and oil, not only in the Dutch manufacturing sector as a whole, but also in each of the six industries.

These results should also be contrasted with two studies on inter-fuel substitution possibilities in North America. Fuss (1977) studied the demand for energy in Canadian manufacturing in a combined time-series (1961–71) cross-section (5 regions of Canada). He found moderate substitutability (no complementarity) between coal, oil, gas and electricity. The

[21] In Magnus and Woodland (1987b) there is formal test for the existence of an aggregate technology from which the TOTAL elasticities could be validly derived. However, this hypothesis is soundly rejected by the data.

Table 7. *Market price elasticities for three selected years*[a]

	1958				1967				1976			
	C	O	G	E	C	O	G	E	C	O	G	E
COAL	−0.78	−0.06	0.58	0.26	−0.85	−0.25	0.89	0.22	−0.55	−0.20	0.89	−0.14
OIL	−0.05	−0.03	0.24	−0.15	−0.14	−0.05	0.28	−0.08	−0.05	−0.02	0.30	−0.22
GAS	0.33	0.14	−0.65	0.18	0.33	0.19	−0.72	0.19	0.28	0.33	−0.66	0.04
ELEC	0.12	−0.06	0.04	−0.09	0.04	−0.06	0.08	−0.07	−0.04	−0.18	0.05	0.16

[a]The elasticity $\partial \ln x_i / \partial \ln p_j$ $(i, j = \mathrm{C, O, G, E})$ appears in the ith row and jth column.

estimates of the own-price elasticities for coal, oil and gas were all less than -1, while electricity was inelastic. Halvorsen (1976), in a study of the industrial demand for energy in the USA, found similar results. Thus, in general findings for The Netherlands agree with those for Canada and the USA with the exception that the present study finds coal and oil to be complements rather than substitutes.

A recent study by Hall (1983) uses data for seven major OECD countries (not including The Netherlands) over the period 1960–79 to estimate a single cost function for fuels with and without the separability assumption. Comparing the results for 1967 with Hall's preferred model, note that the present estimates of the own-price elasticities are of the same general magnitude as Hall's though his estimate of the price elasticity of the demand for oil is larger in absolute terms than that found in this paper. Hall's estimates are also consistent with the result that gas and coal are substitutes.

Turning now to the six industries separately, there is a wide variation in elasticities, both in magnitude and in sign. Recall that the own-price elasticities η^i_{kk} are given by

$$\eta^i_{kk} = \frac{b^i_{kk}}{S^i_k} - (1 - S^i_k) \tag{13}$$

using Equations 6 and 7. It follows that if the quantity of input demanded approaches zero, the elasticity becomes infinite. For example, in 1976, the cost share for coal was uniformly low (ranging from 0.001 in the TEXT and PAPR industries to 0.039 in the BLDG industry), and, except for the chemical industry, it is found that the own-price elasticity for coal is the highest amont the four energy types.

A second result, which is seldom noted, but follows easily from Equation 13, is that a necessary and sufficient condition for the own-price elasticity η^i_{kk} to be negative, is that

$$b^i_{kk} < S^i_k(1 - S^i_k). \tag{14}$$

Hence, if a parameter b^i_{kk} is larger than 0.25, the elasticity η^i_{kk} can never be negative (assuming that the cost share lies between zero and one); if, on the other hand, a parameter b^i_{kk} is negative, the elasticity η^i_{kk} must be negative. In the present study, the high values of b_{EE}(CHEM) = 0.2963 (larger than 0.25) and b_{OO}(CHEM) = 0.2489 (see Table 3) lead to perverse estimates of η_{EE}(CHEM) and η_{OO}(CHEM).

Although the asymptotic standard errors of the cross-price elasticities in Table 5 are quite large, the results nevertheless point towards one important conclusion, namely that in five of the six industries (the exception is METL) *the demand for gas would rise significantly with an increase in the price of coal or oil.*

When interpreting these results, it is important to realize that it is *partial* price elasticies that have been estimated, which account only for substitution between fuels, under the constraint that the total quantity of energy consumed remains constant. The '*complete*' price elasticities, which indicate the percentage change in the demand for energy k due to a 1% change in the price of energy j taking into account the fact that the total energy demand in industry i is also affected by the price change, but assuming that the outputs in each industry are fixed, can be calculated as in Pindyck (1979) by

$$\eta^{*i}_{kj} = \eta^i_{kj} + S^i_j \varepsilon^i \tag{15}$$

where η^i_{kj} is the partial price elasticity given by Equation 7, S^i_j is the cost share of energy j in industry i, and ε^i is the own-price elasticity of energy use in industry i. Under the assumption that ε^i is the same in each industry ($\varepsilon^i = \varepsilon$, say), we obtain the corresponding 'complete' MARKET price elasticity by

$$\eta^*_{kj} = \eta_{kj} + \varepsilon \sum_{i=1}^{q} w^i_k S^i_j \tag{16}$$

Given ε, the 'complete' price elasticities can thus be calculated. In Table 8 estimates of the 'complete' price elasticities in 1976 are presented for the case when the own-price elasticity of energy use is low ($\varepsilon = 0$), moderate ($\varepsilon = -0.5$), and high ($\varepsilon = -1.0$) respectively.[22]

While the main conclusions are not affected, three comments are in order. When the own-price elasticity of energy use is nonzero, (i) all fuels are more responsive to a change in their own price, (ii) the pairs of fuels that were found to be complements (like oil and coal) are complements in a larger degree, and (iii) the pairs of fuels that were found to be substitutes (like gas and coal) are substitutes in a smaller degree, and may, indeed, be complements (gas and electricity).

Energy price indices

The unit cost functions $c^i(\mathbf{p})$ may be interpreted as price indices for energy since they measure the effect of changes in prices for the four fuels (energy types) upon the unit cost of production of the energy aggregate $f^i(\mathbf{x}^i)$. The model developed in this paper allows the estimation of the cost functions up to a factor of proportionality. Thus, it is possible to obtain estimates of the energy price indices

$$p^i_{t,t_0} \equiv c^i(\mathbf{p}_t)/c^i(\mathbf{p}_{t_0}) = \prod_{j=1}^{n} (p_{jt}/p_{jt_0})^{(S^i_{jt} + S^i_{jt_0})/2} \qquad i = 1, \ldots, q;\ t = 1, \ldots, T \tag{17}$$

where t denotes the current period, t_0 is the base period in which the index is unity, and $S^i_{jt} = S^i_j(\mathbf{p}_t)$ is the share of energy j in industry i at time t. Using the estimates of the parameters of the translog cost share equations, estimates of p^i_{t,t_0} were obtained choosing 1967 as the base year. These estimates together with their asymptotic standard errors are presented in Table 9 for each of the six manufacturing industries.

The increases in the prices of the individual energy types from 1967 to 1976 have, according to the energy price indices presented in Table 9, raised the cost of energy most for the BLDG industry (the index is 2.63 in 1976) and least for METL (2.07).[23] The estimates reflect quite clearly the rapid increase in energy prices since 1973.

The separable form assumed for the cost functions allows for the estimation of the complete technology in two stages. In the first stage, each aggregator function can be estimated in the same way as was done for energy; in the second stage, the technology relating these aggregates can be

[22]The estimates of the own-price elasticity of energy (ε) have generally been around -0.4 to -0.5. Magnus (1979 found $\varepsilon = -0.23$ in The Netherlands, while Pindyck (1979) found $\varepsilon = -0.8$.

[23]Since the prices of each energy type are the same in each industry, these price indices differ because each industry has a different cost function estimate, and hence different share estimates.

Table 8. *'Complete' market elasticities in 1976 for three values of* ε[a]

	$\varepsilon = 0$				$\varepsilon = -0.5$				$\varepsilon = -1.0$			
	C	O	G	E	C	O	G	E	C	O	G	E
COAL	−0.55	−0.20	0.89	−0.14	−0.60	−0.37	0.73	−0.26	−0.64	−0.54	0.57	−0.39
OIL	−0.05	−0.02	0.30	−0.22	−0.10	−0.20	0.14	−0.34	−0.15	−0.37	−0.02	−0.45
GAS	0.28	0.33	−0.66	0.04	0.23	0.17	−0.82	−0.08	0.19	0.00	−0.98	−0.21
ELEC	−0.04	−0.18	0.05	0.16	−0.08	−0.34	−0.10	0.02	−0.12	−0.50	−0.26	−0.12

[a]The 'complete' elasticity $\partial \ln x_i / \partial \ln p_j$ $(i, j = \mathrm{C, O, G, E})$ appears in the ith row and jth column. The own-price elasticity of energy use (ε) is assumed to be the same in each industry.

Table 9. *Estimated price indices for energy for six industries in the Dutch manufacturing sector, 1958–76*[a]

	FOOD		TEXT		PAPR		CHEM		BLDG		METAL	
1958	1.5755	(0.1731)	1.5281	(0.1662)	1.5807	(0.1862)	1.8090	(0.2200)	1.7184	(0.1877)	1.6542	(0.1836)
1959	1.4206	(0.1733)	1.3890	(0.1678)	1.4360	(0.1876)	1.6780	(0.2261)	1.5781	(0.1915)	1.5314	(0.1887)
1960	1.2787	(0.1657)	1.2577	(0.1613)	1.3142	(0.1825)	1.5346	(0.2200)	1.4536	(0.1873)	1.3940	(0.1824)
1961	1.2010	(0.1445)	1.1887	(0.1416)	1.2340	(0.1590)	1.4308	(0.1902)	1.3464	(0.1612)	1.3101	(0.1592)
1962	1.1864	(0.1345)	1.1540	(0.1295)	1.2084	(0.1470)	1.3701	(0.1722)	1.3179	(0.1486)	1.2489	(0.1431)
1963	1.2191	(0.1314)	1.1807	(0.1259)	1.2424	(0.1441)	1.3876	(0.1664)	1.3493	(0.1446)	1.2644	(0.1378)
1964	1.1407	(0.1041)	1.1142	(0.1005)	1.1735	(0.1153)	1.2729	(0.1293)	1.2493	(0.1133)	1.1738	(0.1083)
1965	0.9942	(0.0426)	0.9940	(0.0419)	1.0274	(0.0493)	1.0439	(0.0526)	1.0526	(0.0447)	1.0126	(0.0442)
1966	1.0092	(0.0255)	1.0044	(0.0247)	1.0304	(0.0303)	1.0285	(0.0323)	1.0482	(0.0261)	1.0090	(0.0261)
1967	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)	1.0000	(0.0000)
1968	0.9743	(0.0125)	0.9739	(0.0123)	0.9723	(0.0138)	0.9599	(0.0142)	0.9768	(0.0125)	0.9678	(0.0126)
1969	0.8853	(0.0239)	0.8818	(0.0233)	0.8839	(0.0276)	0.8623	(0.0285)	0.8988	(0.0240)	0.8715	(0.0241)
1970	0.9900	(0.0440)	0.9704	(0.0421)	0.9846	(0.0511)	0.9503	(0.0525)	1.0169	(0.0446)	0.9451	(0.0431)
1971	1.1191	(0.0638)	1.0878	(0.0605)	1.1066	(0.0733)	1.0691	(0.0753)	1.1544	(0.0649)	1.0531	(0.0614)
1972	1.0358	(0.0581)	1.0121	(0.0551)	1.0322	(0.0698)	0.9994	(0.0726)	1.0810	(0.0597)	0.9897	(0.0572)
1973	1.1893	(0.0677)	1.1395	(0.0632)	1.1784	(0.0788)	1.1325	(0.0809)	1.2297	(0.0691)	1.0873	(0.0635)
1974	1.5131	(0.1342)	1.4295	(0.1248)	1.4592	(0.1439)	1.4442	(0.1491)	1.5383	(0.1353)	1.3232	(0.1193)
1975	2.0641	(0.1529)	1.9152	(0.1384)	2.0236	(0.1745)	1.9663	(0.1805)	2.1264	(0.1554)	1.7531	(0.1330)
1976	2.5510	(0.1953)	2.3212	(0.1727)	2.4995	(0.2273)	2.4472	(0.2385)	2.6303	(0.1983)	2.0682	(0.1627)

[a]Asymptotic standard errors for these estimates are in parentheses. In 1967 the standard errors are zero, because of the normalization.

estimated.[24] If one were to estimate the complete technology for each industry in this way, assuming that energy forms a homothetically separable group of inputs, the price indices presented here could be used as 'the price of energy' in each industry at the second stage of estimation. Alternatively, one might compute a nonparametric price index based solely upon observable data. Two such indices, which are discrete approximations to the Divisia index, were calculated for each industry. They are defined as

$$p^i_{t,t_0} = \prod_{j=1}^{n} (p_{jt}/p_{jt_0})^{(S^i_{jt} + S^i_{jt_0})/2} \tag{18}$$

and

$$p^i_{t,t-1} = \prod_{j=1}^{n} (p_{jt}/p_{j,t-1})^{(S^i_{jt} + S^i_{t,t-1})/2} \tag{19}$$

where s^i_{jt} is the *observed* share of energy j in industry i at time t. The first of these indices is the Fisher–Turnquist–Divisia index and is the same as Equation 17 except that observed rather than predicted shares are used to form the weights. The index defined by Equation 19 is a chain version of Equation 18 and is commonly used in empirical work. These two non-parametric indices are not presented since they are generally close to those in Table 9 except in the early years.

One can think of these non-parametric indices as 'observed' indices in comparison with the parametric indices (Equation 17) which are 'estimates'. Indeed, Diewert (1976, p. 121) has shown that the index (Equation 18) is exact if the data are generated without disturbances from a translog cost function. The index (Equation 17) is exact for the translog cost function estimates. Thus the closeness of the two indices depends upon how much the observed shares deviate from the predicted shares. An overall measure of the power of the translog model to explain the observed price indices is given by their correlation coefficients. These are presented in Table 10 for each industry and for both non-parametric indices. Clearly, the correlations are very high indicating that the model predicts the price indices quite well.

A comparison of price index (Equation 17) with a Laspeyre's price index indicates the extent to which each manufacturing industry has been able to adjust to fuel price variations by substituting away from more expensive towards less expensive fuels. If no substitution were to occur then the Laspeyre's price index with its fixed base period quantities would be an accurate index of the cost of fuels to a particular industry. To the extent that fuel substitution is possible the price index given by Equation 17 will be lower than the Laspeyre's price index.

To illustrate this point, the Laspeyre's price indices were calculated for each industry, using the 1967 predicted shares as fixed weights. The resulting price indices in 1976 are 2.80, 2.51, 2.73, 2.34, 2.87 and 2.15 which may be compared with the last row of Table 9. This comparison shows that the percentage cost savings as a result of substitution away from inputs that have become relatively expensive are: FOOD−9%, TEXT−8%, PAPR−9%, BLDG−8%, and METL−4%. Since the estimate of the cost function for CHEM is not concave at any sample point, the corresponding calculation for this industry is inappropriate.

[24]See Fuss (1977) for an example of a two-stage estimation. It should be noted that, at the second stage, account must be taken of the fact that the price index for energy is an estimate and hence a random variable.

Table 10. *Correlations between energy price indices*

	FOOD	TEXT	PAPR	CHEM	BLDG	METL
Index 1 (Equation 18)	0.98	0.98	0.96	0.98	0.97	0.97
Index 2 (Equation 19)	0.96	0.97	0.94	0.96	0.95	0.96

V. CONCLUSIONS

In this paper the substitution possibilities between fuels (coal, oil, gas and electricity) in response to changes in the relative prices of these fuels,have been estimated, using data for six industries of the Dutch manufacturing sector over the period 1958–76. The use of this disaggregated data set raises some special issues for applied econometric analysis of the demands for fuels.

The use of combined cross-section and time-series data requires special attention to be given to the stochastic specification. The translog share equations were estimated for all industries jointly using a multivariate error components model incorporating serial correlation in the two components, as developed by Magnus and Woodland (1987a). The model thus allows for the usual correlations between disturbances in the fuel equations, for the correlation between disturbances in the different industries (via the error components structure), and for correlations between disturbances in different time periods.

The use of disaggregated data allows specification of a different fuel cost function for each industry in the Dutch manufacturing sector. A flexible function form was chosen for the cost function, namely the translog, and the resulting share equations were estimated. Thus, only minimal restrictions are placed upon the matrices of Allen–Uzawa substitution and price elasticities. The results indicate that, at the sectoral level, the (conditional) demands for fuels are inelastic with respect to their own prices. They also show that coal and oil are substitutes for gas in the sense that demand for these fuels increases when the price of gas increases. Gas is found to be substitutable for coal, oil and electricity. While elasticities at the industry level vary in size and sign, the results show that gas is a substitute for both coal and oil in five out of the six manufacturing industries.

Estimates were also presented of the energy price indices implied by the model, along with their standard errors. These parametric indices are an alternative to the usual non-parametric indices that are usually employed. They have the advantage of being consistent with the technological and behavioural assumptions of the model, and of having standard errors that reflect the reliability of the indices and changes therein.

APPENDIX: THE DATA

Table A1. *Input costs and prices for six industries in Dutch manufacturing, 1958–76: coal*

Year	Input costs (thousands of current guilders)							Price (guilders per Gcal)
	FOOD	TEXT	PAPR	CHEM	BLDG	METL	Total	
1958	41 813	15 372	24 128	33 435	29 155	8821	152 724	10.81
1959	32 118	13 388	23 477	28 590	26 351	8582	132 506	9.91
1960	28 439	11 966	21 838	26 537	26 605	8328	123 713	9.65
1961	20 581	8539	19 085	19 569	22 203	6720	96 697	8.96
1962	17 536	6826	16 344	19 991	22 437	6128	89 262	8.83
1963	16 417	6610	14 229	20 209	21 886	6776	86 127	9.27
1964	14 524	4664	8370	18 518	20 771	6713	73 560	9.31
1965	11 332	3326	7572	17 675	19 493	4803	64 201	10.33
1966	4186	1485	7941	17 098	22 930	4444	58 084	10.76
1967	2868	564	6520	11 300	20 745	3011	45 008	9.56
1968	3065	377	7061	11 945	19 424	3012	44 884	10.46
1969	4184	296	4366	20 885	16 348	2884	48 963	11.40
1970	3247	140	1514	25 616	14 783	3700	49 000	15.61
1971	3427	41	933	24 863	8416	4218	41 898	20.28
1972	2601	20	140	28 654	4702	2961	39 078	20.01
1973	2630	5	168	27 352	3956	2756	36 867	21.04
1974	3701	7	114	40 257	3217	3018	50 314	28.47
1975	4278	9	439	48 296	9688	8884	71 594	36.56
1976	6114	41	124	60 023	10 162	8634	85 098	41.31

Table A2. *Input costs and prices for six industries in Dutch manufacturing, 1958–76: oil*

Year	Input costs (thousands of current guilders)							Price (guilders per Gcal)
	FOOD	TEXT	PAPR	CHEM	BLDG	METL	Total	
1958	51 929	18 642	13 884	39 078	18 330	19 149	161 012	9.75
1959	47 858	17 251	13 380	34 495	17 567	18 570	149 121	8.29
1960	50 068	16 166	14 518	33 867	16 361	16 096	147 076	6.98
1961	51 628	16 880	14 380	36 578	17 841	14 977	152 284	6.63
1962	55 002	19 642	18 483	45 747	23 034	19 356	181 264	6.98
1963	60 013	21 520	25 441	56 020	26 944	23 864	213 802	7.30
1964	62 638	20 818	30 667	65 998	30 271	23 946	234 338	6.83
1965	56 254	17 833	29 402	72 189	30 347	22 914	228 939	6.22
1966	63 866	16 891	32 968	86 864	31 450	26 551	258 590	6.90
1967	73 188	20 368	33 341	74 898	31 874	26 896	260 565	7.60
1968	73 329	19 131	34 143	63 068	31 744	27 726	249 141	7.64
1969	59 113	16 895	28 649	55 908	31 325	25 698	217 588	7.06
1970	64 770	17 706	28 790	68 815	32 105	28 671	240 857	8.48
1971	54 692	14 364	19 480	84 028	25 649	26 034	224 247	10.13
1972	27 696	6624	5388	64 736	13 514	14 723	132 681	8.58
1973	34 717	7309	5235	107 627	17 196	17 387	189 471	11.21
1974	51 400	10 257	6603	206 875	24 339	23 388	322 862	19.03
1975	54 944	10644	5430	218 294	26 886	25 810	342 008	23.92
1976	64 702	13 143	10 388	833 269	37 497	30 625	989 624	31.67

Table A3. *Input costs and prices for six industries in Dutch manufacturing, 1958–76: gas*

Year	Input costs (thousands of current guilders)							Price (guilders per Gcal)
	FOOD	TEXT	PAPR	CHEM	BLDG	METL	Total	
1958	1732	8	8	31 910	10 454	11 700	55 812	30.39
1959	1891	7	59	31 017	10 250	11 698	54 922	29.54
1960	2181	55	82	29 005	9514	12 103	52 940	27.26
1961	2024	165	94	31 708	8592	10 711	53 294	23.54
1962	1975	230	92	33 361	8036	9689	53 383	22.96
1963	2133	204	91	33 899	8078	9938	54 343	22.69
1964	1693	126	90	31 319	8429	7636	49 293	18.01
1965	1260	252	194	23 111	7 190	4893	36 900	9.69
1966	5753	1353	1921	37 452	10 860	5308	62 647	8.73
1967	10 314	2397	4060	55 052	13 407	5760	90 990	7.49
1968	15 298	2900	5313	89 813	17 333	7943	138 600	6.76
1969	20 961	3200	9892	112 014	18 453	9013	173 533	5.86
1970	34 771	5040	16 846	153 066	28 376	12 679	250 778	6.42
1971	57 993	10 251	27 107	199 050	45 712	19 388	359 501	7.05
1972	69 693	13 005	36 482	238 989	56 595	24 636	439 400	6.70
1973	87 658	14 928	46 709	327 143	70 363	34 613	581 414	7.89
1974	106 654	16673	53 622	417 310	82 775	37 780	714 814	8.94
1975	173 434	25 263	69 689	612 210	117 750	62 179	1060 525	14.09
1976	233 722	33 784	102 404	851 884	148 501	86 386	1456 681	18.80

Table A4. *Input costs and prices for six industries in Dutch manufacturing, 1958–76: electricity*

Year	Input costs (thousands of current guilders)							Price (guilders per Gcal)
	FOOD	TEXT	PAPR	CHEM	BLDG	METL	Total	
1958	29 936	23 416	17 191	83 955	16 673	50 092	221 263	74.10
1959	33 202	21 266	17 493	85 613	16 601	49 118	223 293	68.60
1960	32 114	23 225	17 278	90 645	17 027	49 391	229 680	62.60
1961	33251	23 386	18 209	90 558	16 869	49 512	231 785	60.90
1962	31 865	22 103	16 606	90 770	17 279	48 414	227 037	56.10
1963	34 304	23 247	18 768	101 550	19 335	52 051	249 255	56.70
1964	35 678	22 991	18 891	113 681	21 883	52 907	266 031	55.40
1965	36 312	22 321	18 530	122 233	23 176	58 473	281 045	53.40
1966	40 401	22 653	18 815	142 737	24 891	62 787	312 284	53.30
1967	48 075	23 143	21 626	164 605	28 130	65 961	351 540	54.20
1968	56 011	25 526	22 185	197 368	31 999	69 061	402 150	52.20
1969	53 084	23 054	19 774	197 274	31 046	66 066	390 298	46.20
1970	60 880	23 372	21 515	219 341	34 796	74 113	434 017	47.60
1971	70 212	25 700	29 041	229 347	40 657	86 660	481 617	51.40
1972	72 766	23 568	29 460	249428	39 771	87 693	502 686	49.10
1973	85 068	24 225	32079	273 411	44 625	91 392	550 800	51.00
1974	95 592	25 088	34 720	312 816	50 736	95 088	614 040	56.00
1975	124 387	29 120	39 473	284 868	60 684	105 621	644 153	71.90
1976	137 950	31 233	50 685	367 583	65 023	121 985	774 459	77.50

ACKNOWLEDGEMENTS

Magnus's research was supported in part by the Netherlands Organization for the Advancement of Pure Research (ZWO). Woodland's research was supported by grants from the Social Services and Humanities Research Council of Canada and the University of Sydney. We are greatly indebted to Greg Defina, Mira Kempisty, Shyama Roy and David Ryan for exceptional research assistance, and to J. S. Cramer and the referee for helpful comments.

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